The Use of Accounting Data to Predict Bank Financial Distress in MENA Countries

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1. Introduction

In the Middle Eastern and North African (MENA) region, little has been written on the prediction of bank failures. The recent financial crisis, declining bank health and government subsidization or injection of cash flow by the government sector to revive or save banking institutions from failing, have heightened interest in the role of the banking sector in the economy especially since most studies in this area pinpoint particular weaknesses in the sector which aggravated the crisis. However, most studies focus on early-warning models of banking crises (Demirgüc-Kunt and Degatriache 2000) and do not consider the prediction of bank's financial deterioration at the individual bank level.

The objectives of this paper are multiple. First, to construct an early-warning system of bank financial distress specifically designed for MENA banks. The paper also looks into the reliability and stability of early indicators depending on the size of the bank and on its balance sheet structure. Using experiences of 13 banking sectors in MENA countries as a point of study, this paper starts by building an early-warning model based on downgrades by the Fitch rating agency and a large set of accounting indicators.

Our paper proposes a framework that can be implemented for MENA banks, and which enables us to further raise two theoretical issues. First, our approach, which is applied on a wide range of MENA banks, enables to use annual frequency accounting data without imposing interpolation of these data. This point is important because for many MENA banks only yearly accounting data are available. Second, instead of focusing on bank failures or on severe financial distress, we consider the prediction of any downward change in a bank's financial health.[1] Our view is that early detection of downgrades might play a major role in the implementation of prompt corrective action by regulators, and that it can do so without jeopardizing the strategies followed by bank managers. We deal with the issue of identifying

[1] Given regulators hardly declare bank failures but rather arrange restructuring or mergers with other healthy banks, then considering the prediction of any downward change in a bank's financial health is a good alternative to understand the extent of distress or potential failure.

deterioration in banks' future financial health by considering the information contained in the changes in indicators such as financial ratios, rather than in their level. Third, we also wish to test the robustness of results in light of the modern financial intermediation theory developed by Leland and Pyle (1977), Diamond and Dybvig (1983), and Diamond (1984). These studies consider that banks and financial intermediaries are agents that play a major role in the financial system as information intermediaries. Banks collect and process information about loan customers (Diamond 1984), which implies that they possess private information. Therefore, due to banks' inherent opacity, we question the ability of accounting indicators to explain banks degradation of financial situation. We also consider the potential influence of the size of the bank on the effectiveness of accounting indicators. Indeed, we can assume that bank size affects the reliability of accounting indicators. We might suppose that accounting information is less reliable for smaller banks because accounting standards are generally less stringent for smaller banks (lower quality and lower disclosure frequency).This would be the first comprehensive attempt to better understand the banking distress in the region using a long time series data including information on banks from years as late as 2008.

1. Methodology

As a first step, we test for the contributions of various accounting indicators to the prediction of bank financial distress. We then study the stability of the predictive power of early warning indicators with respect to bank size and balance sheet structure. To start off, it is necessary to establish an event that could represent a change in the financial condition of a bank. Most studies in the US conducted in this area either make use of explicit bank failures or supervisory ratings downgrades as in Curry, Elmer and Fissel (2007), Kolari et al. (2002) and Gunther, Levonian, and Moore (2001). On the other hand, studies on European banks make use of sharp downgrades (Gropp, Vesala and Vulpes 2006) as proxies for actual bank failure or downgrade announcements by private agencies[2] (Distinguin, Rous and Tarazi 2006) as proxies for financial distress. Since actual bank failure is quite limited in MENA, this paper will follow Distinguin, Rous and Tarazi (2006) using downgrading announcements to represent deteriorations in the bank's financial condition. These downgrading announcements are obtained from the Fitch rating agency.

[2] Due to confidentiality laws in most countries, it is difficult to gain access to explicit supervisory ratings in Europe.

Accounting C_{ji} indicators are computed to estimate the probability of a downgrade. However, accounting data are available only annually. As such, the starting point for this study is December 31st of each year - when accounting information is available. Events taking place during the following calendar year are then considered, which avoids the interpolation of missing accounting data and ensures that the information content of accounting data is not inappropriately upward biased.

For each bank in the sample, the dependent variable Y is equal to:

- 1, if the bank is downgraded by Fitch with no upgrading taking place during the entire calendar year and no downgrade or upgrade during the last quarter of the preceding year;
- 0, if the rating remains unaltered during the calendar year and;
- NA (not available), for all other cases.

The following logit model is employed to estimate the probability of a downgrade:

$$\text{Prob}\{Y_i = 1\} = \Phi\left(\alpha + \sum_{j=1}^{J} \beta_j C_{ji}\right)$$

where C_{ji} is the j^{th} accounting indicator and $\Phi(.)$ denotes the cumulated logistic distribution function. Maximum likelihood estimators of the coefficients (α, β_j) are used and robust Huber-White covariance matrix estimation allows for possible misspecification of the error term distribution.

The best accounting indicators are selected through a stepwise process.[3]

However, due to the possible existence of a size effect and a balance sheet structure effect, there is a need to test for the stability of the relationship. We also conduct estimations of the different models on restricted samples of banks and using dummy variables.

3. Sample and Indicators

3.1. Sample

[3] As a rule of thumb, a 10 percent level for type 1 error is retained and a Max (Min) LR statistic is used as a criterion for adding (ruling out) each potential indicator to (from) the selected set.

Our sample consists of 67 commercial banks from 13 countries: Bahrain, Egypt, Israel, Jordan, Kuwait, Lebanon, Morocco, Oman, Qatar, Saudi Arabia, Tunisia, Turkey, and United Arab Emirates. These banks are rated by the Fitch rating agency.

Table 1 presents the distribution of banks by country. Information is taken from Bankscope Fitch IBCA.

Insert Table 1

Accounting data (annual financial statements) for the banks in our sample are obtained from Bankscope Fitch IBCA. Our econometric specification imposes the use of accounting data ranging from 1996 to 2007 to predict downgrades that occurred between 1998 and 2008. Table 2 shows descriptive statistics for our sample of banks. The banks are categorized into three groups A, B, and C. The bank is classified as group A, if it is from Egypt, Lebanon, Morocco or Tunisia; then group B, if from Bahrain, Kuwait, Oman, Qatar, Saudi Arabia or United Arab Emirates, and group C, if from Israel or Turkey. It seems more prudent to group the banks into country categories as the three country groups exhibit different characteristics particularly with respect to the level of development of their financial system. The data exhibit a high level of heterogeneity, enabling us to investigate the accuracy of accounting indicators to predict downgrades for different sizes and types of institutions.

Insert Table 2

3.2. Financial deterioration indicator

Table 3 provides information on the downgrades used in this study. These downgrades are announced by the rating agency Fitch. Ratings information is obtained from Bankscope Fitch IBCA. Since several restrictions are applied on the construction of the binary dependent variable Y, only a limited number of "clean" downgrades are subsequently considered in this study. For example, if several downgrades occur during the calendar year, we only consider the first one. Of the total 109 downgrades, only 52 "clean" downgrades are used for the estimations. Besides, among these 52 downgrades several happened the same day, for example a bank can be downgraded both for the Fitch Short Term and the Fitch Long Term rating at the same day. This implies that only 46 events can be used in this study.

Table 4 provides information on the distribution of Fitch Individual, Fitch Long Term, and Fitch Short Term downgrades. We can notice that most of the ratings are in the speculative grades for debt ratings and as low as C or less for individual ratings.

Insert Table 3 and Table 4

3.3. Accounting indicators

In this study, we consider a set of accounting ratios (see Table 5) commonly used in the assessment of bank financial health. We group these ratios into the four categories of the CAEL (Capital, Asset quality, Earnings and Liquidity) rating. Previous studies in this area either consider accounting ratios in level (Curry, Elmer and Fissel 2007, Gunther, Levonian, and Moore 2001) or in variation (first order difference) (Distinguin, Rous and Tarazi 2006). In this study, as we aim to predict changes in the financial condition of the bank, it seems more appropriate to consider the changes in the values of the ratios. More importantly, our study requires equal consideration of banks regardless of their initial financial strength. More precisely, the downgrade of a sound and safe bank as compared to a modestly performing bank can only be captured by a change in the values of the ratios of this bank. Consequently, C_{ji} is defined as the annual change in the value of the accounting ratio R_{ji}.

Insert Table 5

4. Empirical Results

We first consider the predictive power of accounting indicators *via* a stepwise process. Then, dummy variables are introduced and sub-samples are defined to capture the influence of the size of the bank and of its balance sheet structure on the effectiveness of early indicators.

As a preliminary step, univariate regressions are conducted. They are ran on the whole sample of banks without taking into account the regional sub-groups defined in 3.1. (whole sample column in Table 6), they are also ran taking into account country group differences by introducing two dummy variables GROUPA and GROUPC which are equal to one for banks belonging to the considered group (regional dummies column in Table 6) or running the regressions on the three different subgroups.

4.1. Simple regression results

Table 6 shows the results for the univariate regressions on the accounting indicators for MENA banks. Results are only reported when the coefficients are at least significant at the 10 percent level.

Insert Table 6

We can notice that the results obtained with regional dummies are quite similar to those obtained without introducing these dummies. Indeed, the dummy variables are never significant in the regressions. Thus, in the following estimations we no longer take these dummies into account.

Considering the whole sample results, we can see that at least one indicator in each category (Capital, Asset quality, Earnings, and Liquidity) appears as significant. For capital adequacy indicators, those reflecting a change in hybrid capital appear significant at the 5 percent level. Two indicators of asset quality are also significant: the change in the ratio of loan loss reserves to gross loans (LLR_GL) and the change in the ratio of impaired loans to gross loans (IMPLOANS_GL). As expected, they are both positively linked with banks financial distress. Four indicators reflecting changes in the profitability/earnings ratios are also significant at least at the 5 percent level. The signs of the coefficients are all consistent with the expected negative relationship between profitability and bank financial distress and the expected positive relationship between cost or expenses and bank financial distress. The changes in the liquidity ratio NL_CSTFUND is also significant at 10 percent. But, the negative sign of the coefficient is not consistent with the expected negative relationship between liquidity and bank financial distress.

When we consider the results for the different sub-groups, we can notice that for Group A and Group B banks, at least one indicator is significant in each category. For Group C banks only three indicators appear as significant, two indicators corresponding to a change in the capital to risk weighted assets ratios (TCR and TIER1RATIO) and an indicator reflecting asset quality (LLP_NIR).

4.2. Contribution of accounting indicators

After conducting the univariate regressions and initially determining the set of indicators that are significant, a stepwise procedure is considered. Table 7 presents the results for the stepwise procedure based on the full set of accounting indicators. We run the stepwise process on the whole sample of banks and on the three sub-samples corresponding to the regional groups (Group A, Group B, and Group C) previously discussed.

Insert Table 7

The stepwise results show that, on the whole, asset quality and earnings indicators are the optimal predictors of bank financial distress. Indeed, when we consider the results obtained on the whole sample of banks, ΔCOSTTOINCOME is significant at the 1 percent level. This ratio measures the costs of running the bank as a percentage of income generated before provisions. As expected, there is a negative relationship between the efficiency of the bank and the probability of a future downgrade. ΔLLP_NIR and ΔIMPLOANS_GL, both reflecting problems in bank asset quality, are, as expected, positively and significantly related to banks financial distress.

Results for Group A and Group B are quite the same as for each group both asset quality and earnings indicators are selected by the stepwise process: the change in the ratio of net interest revenue to average assets (NIR_A) and the change in the ratio of loan loss reserves to gross loans (LLR_GL) for Group A and the changes in the cost to income ratio (COSTTOINCOME) and in two ratios reflecting asset quality (IMPLOANS_GL, LLP_TA) for Group B. For Group C, one indicator reflecting capitalization appears as significant (ΔEQU_DEPSTFUND) at the 10 percent level but its coefficient has the wrong sign. For group C, an indicator of asset quality, the change in the ratio of loan loss provisions to net interest revenue (LLP_NIR), is also significant.

As previously mentioned, the possible existence of size and balance sheet structure effects might limit the accuracy of early indicators in the prediction process. Thus, we consider the influence of size and balance sheet structure on the effectiveness of accounting indicators by running the regressions on different sub-samples. Due to the limited number of observations available on the different regional sub-groups, in the following regressions, we do not separate banks on the basis of these sub-groups.

4.3. Size effect

We might suppose that the accuracy of accounting indicators to predict bank financial distress is lower for small banks. Indeed, accounting information may be less reliable for smaller banks because accounting standards are generally less stringent for them (lower quality and lower disclosure frequency). Thus, accounting indicators may be more effective for banks that have a major position in their domestic banking system.

Thus, to consider the possible existence of a size effect on the accuracy of early indicators, estimations are conducted on two sub-samples:

- Too Big To Fail banks, that is, banks with a Fitch Support rating equal to 1 or 2. This support rating indicates the likelihood of public or private support on a scale from 1 to 4; a grade of 1 (the highest) indicates the presence of an assured legal guarantee. FitchRatings Support Ratings are commonly used in the literature to identify too-big-to-fail banks operating outside the US (see Gropp, Vesala, and Vulpes 2006; and Distinguin, Rous, and Tarazi 2006).
- Non Too Big To Fail banks, that is, banks with a Fitch Support rating lower than 2.

The results obtained for the size effect are presented in Table 8.

Insert Table 8

Considering the same indicators that are selected on the whole sample of banks, we can notice that these indicators are significant only for large banks. None of these indicators appear significant for small banks. This suggests that accounting information may be reliable only for large banks. However, this result could be due to the fact that the indicators selected by the stepwise process applied to the whole sample of banks are not the best indicators for the sub-sample of small banks. Therefore, we run the stepwise process on the two sub-samples of banks separately. The results, which are shown in Table 9, confirm the absence of significant indicators to predict downgrades for small banks. Indeed, the stepwise process is unable to select any significant (10 percent level) accounting indicator for small banks.

Insert Table 9

Table 9A presents the same results using dummy variables rather than sub-samples. In Table 9B, where GDPPERCAPITA is introduced, we can notice that this variable is not significant for large banks but is significant at the 10 percent level for small banks. Table 9C shows the same results running the regressions on the sub-samples.

4.4. Balance sheet structure effect

We try to capture the effectiveness of early indicators for different balance sheet profiles. First, we consider the structure of assets *via* the importance of the ratio of net loans to total assets. Then, we study the impact of the structure of liabilities by considering alternatively the importance of the ratio of deposits to total assets and of the ratio of market funded liabilities to total assets. In each case, we consider the impact of the balance sheet structure (assets or liabilities) by running the regressions on two sub-samples constructed on the basis of the considered ratio: a sub-sample of banks with a high value of the ratio and a sub-sample of banks with a low value of the considered ratio. The threshold is the median value of the ratio.

4.4.1 Structure of bank assets

We separate banks on the basis of their loan activity.

Insert Table 10 and Table 11

Considering the same indicators that are selected on the whole sample of banks (Table 10), we can notice that they are almost all significant for the two sub-samples of banks. When we run the stepwise process separately on the two sub-samples (Table 11), we see that one indicator reflecting earnings (ΔROE) appears as the best predictor of bank financial distress for banks heavily involved in loan activity whereas three different indicators are selected for banks with a lower value of the ratio of net loans to total assets.

Thus, it seems that bank asset structure does not deeply affect the accuracy of accounting indicators; accounting information is useful to predict bank financial distress of banks whatever their structure of assets.

4.4.1 Structure of bank liabilities

First, we separate banks on the basis of their deposit activity.

Insert Table 12 and 13

The results obtained when we consider the indicators selected by the stepwise process ran on the whole sample of banks (Table 12) indicate that these indicators are not significant for banks focused on deposit activities, which may indicate that accounting information is only useful for banks with a relatively low deposit activity and more reliant on market debt or other sources of funding. However, when we consider the results obtained in Table 13, that is when we run the stepwise process separately on the two sub-samples, we see that the accurate indicators are different in the two sub-samples but accounting information is useful for both sub-samples.

When we consider the results obtained when we separate the banks on the basis of the ratio of market funded liabilities to total assets (Table 14 and Table 15), the conclusions remain the same.

Insert Table 14 and 15

5. Conclusions

The aim of this study is to first understand how the rating agencies determine banks' financial health based primarily on accounting information to predict the financial distress of MENA banks. It also tests for the presence of a too-big-to-fail effect. Results reflect the crucial role of the level and change of capital, asset quality, earnings, and liquidity ratios in improving the prediction of future distress. Additional factors that contribute to the improvement of the prediction models are the change in costs to income, change in net interest revenue to assets, and the change in ratio of loan loss reserves to gross loans. We observe that influence of factors vary across size of the banks as smaller banks are impacted by the outstanding credit and funding strategies. As MENA regulators make policies and provide guidelines for local banks on safety and soundness, learning from the style, approach, and experience of international rating agencies could be important.

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Table 1. Distribution of Banks by Country

COUNTRY	NUMBER
BAHRAIN	6
EGYPT	2
ISRAEL	3
JORDAN	4
KUWAIT	5
LEBANON	2
MOROCCO	2
OMAN	4
QATAR	4
SAUDI ARABIA	9
TUNISIA	1
TURKEY	16
UNITED ARAB EMIRATS	9
TOTAL	67

Table 2. Descriptive Statistics on Summary Accounting Information for the Period 1997-2007.

Whole sample

	Mean[2]	Median	Standard Deviation[2]	Minimum	Maximum
Total Assets (in million USD)	12632.25	5976.10	17454.85	28.6	162567.40
Net Loans[1]/ Total Assets (%)	49.79	50.55	15.58	2.65	82.82
Deposits/ Total Assets (%)	80.20	82.82	9.76	0.00	97.65
Subordinated Debt/ Total Assets (%)	0.83	0	1.23	0.00	5.67
Tier 1 Ratio (%)	16.62	15.25	8.18	6.10	72.40
ROA (%)	1.94	1.97	2.16	-24.12	13.15

[1] Net loans are defined as gross loans less loan loss reserves.

[2] Each mean is calculated as $\overline{X} = \frac{1}{NT}\sum_{t=1}^{T}\sum_{j=1}^{N} X_{jt}$ where N is the number of banks and T is the number of financial reports.

Standard deviations were computed on a similar basis.

Group A:

	Mean[2]	Median	Standard Deviation[2]	Minimum	Maximum
Total Assets (in million USD)	9218.29	5160.48	9306.60	874.50	39995.00
Net Loans[1]/ Total Assets (%)	38.90	39.41	10.57	19.58	66.62
Deposits/ Total Assets (%)	85.33	86.36	4.07	73.12	91.88
Subordinated Debt/ Total Assets (%)	0.68	0.25	0.81	0.00	2.87
Tier 1 Ratio (%)	14.48	14.5	5.50	6.10	31.10
ROA (%)	1.19	1.06	1.40	-0.19	13.01

[1] Net loans are defined as gross loans less loan loss reserves.

[2] Each mean is calculated as $\overline{X} = \frac{1}{NT}\sum_{t=1}^{T}\sum_{j=1}^{N} X_{jt}$ where N is the number of banks and T is the number of financial reports.

Standard deviations were computed on a similar basis.

Group B:

	Mean[2]	Median	Standard Deviation[2]	Minimum	Maximum
Total Assets (in million USD)	8897.69	5502.85	9296.30	239.30	55657.90
Net Loans[1]/ Total Assets (%)	51.81	52.26	14.97	2.65	82.82
Deposits/ Total Assets (%)	80.05	82.28	7.85	46.70	94.05
Subordinated Debt/ Total Assets (%)	0.58	0	1.12	0.00	5.67
Tier 1 Ratio (%)	17.54	16.20	6.59	8.70	48.50
ROA (%)	2.35	2.23	1.47	-6.11	13.15

[1] Net loans are defined as gross loans less loan loss reserves.

[2] Each mean is calculated as $\overline{X} = \frac{1}{NT}\sum_{t=1}^{T}\sum_{j=1}^{N} X_{jt}$ where N is the number of banks and T is the number of financial reports.

Standard deviations were computed on a similar basis.

Group C:

	Mean[2]	Median	Standard Deviation[2]	Minimum	Maximum
Total Assets (in million USD)	28288.86	17268.10	30648.61	28.60	162567.40
Net Loans[1]/ Total Assets (%)	51.85	56.04	17.39	9.17	76.67
Deposits/ Total Assets (%)	76.50	80.70	15.56	0.00	97.65
Subordinated Debt/ Total Assets (%)	1.61	1.34	1.50	0.00	5.41
Tier 1 Ratio (%)	15.32	11.80	12.29	6.10	72.40
ROA (%)	0.97	1.16	3.87	-24.12	10.75

[1] Net loans are defined as gross loans less loan loss reserves.

[2] Each mean is calculated as $\overline{X} = \frac{1}{NT}\sum_{t=1}^{T}\sum_{j=1}^{N} X_{jt}$ where N is the number of banks and T is the number of financial reports.

Standard deviations were computed on a similar basis.

Table 3. Downgrades Information

(Number of clean downgrades in parenthesis)

	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
Fitch Individual	3 (1)	1 (1)	1 (1)	10 (4)	11 (6)	3 (3)	2 (1)		1 (1)		21 (11)
Fitch Long Term	2 (2)			24 (11)	9 (3)	11 (2)					1 (0)
Fitch Short Term				2 (2)	3 (1)	3 (2)					1 (0)
TOTAL	5 (3)	1 (1)	1 (1)	36 (17)	23 (10)	17 (7)	2 (1)		1 (1)		23 (11)

Table 4. Distribution of Downgrades
(Number of clean downgrades in parenthesis)

Fitch individual

FROM	A/B	B	B/C	C	C/D	D
TO						
B	1 (0)					
B/C		7 (4)				
C			17 (13)			
C/D				13 (8)		
D			1 (0)		7 (2)	
D/E					4 (2)	
E					1 (0)	1 (0)
F						1 (0)

Fitch Long Term

FROM	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-
TO												
A-	1 (1)	2 (2)										
BBB+			3 (3)									
BBB				2 (0)								
BBB-												
BB+						2 (1)						
BB												
BB-								2 (2)				
B+									10 (8)			
B									2 (0)	8 (0)		
B-										2 (0)	11 (1)	
CCC+												2 (0)

Fitch Short Term

FROM	F1	F2	F3	B
TO				
F2	3 (3)			
F3		3 (1)		
B			2 (1)	
C				1 (0)

Table 5. Accounting Ratios

CATEGORY	DEFINITION	NAME
CAPITAL	Capital funds/ Deposits and short term funds	CAPFUNDS_DEPSTFUND
	Capital funds/ total liabilities	CAPFUNDS_LIAB
	Capital funds/ net loans	CAPFUNDS_NL
	Capital funds/ total assets	CAPFUNDS_TA
	Equity/ deposits and short term funds	EQU_DEPSTFUND
	Equity/ total liabilities	EQU_LIAB
	Equity/ net loans	EQU_NL
	Equity/ total assets	EQU_TA
	Subordinated debt/ capital funds	SUB_CAPFUNDS
	Total capital ratio	TCR
	Tier1 ratio	TIER1RATIO
	Hybrid capital/ total liabilities	HYBRIDCAP_LIAB
	Hybrid capital/ total assets	HYBRIDCAP_TA
ASSET QUALITY	Loan loss reserves/ impaired loans	LLR_IMPLOANS
	Impaired loans/ gross loans	IMPLOANS_GL
	Loan loss provision/ net interest revenue	LLP_NIR
	Loan loss reserve/ gross loan	LLR_GL
	Net charge off/ gross loan	NCO_GL
	Net charge off/ net income before loan loss provision	NCO_NIBLLP
	Loan loss provision/ total assets	LLP_TA
	Loan loss provision/ gross loan	LLP_GL
	Loan loss reserves/ total assets	LLR_TA
EARNINGS	Cost to income ratio	COSTTOINCOME
	Income net of distribution/ average equity	INCNET_EQU
	Net interest margin	NIM
	Net interest revenue/ average assets	NIR_A
	Non interest expenses/ average assets	NONINTEXP_A
	Non operating items and taxes/ average assets	NONOPIT_A
	Non operating items/ net income	NONOPIT_NETINC
	Other operating income/ average assets	OTHOPINC_A
	Pre-tax operating income/ average assets	PRETAXOPINC_A
	Roa	ROA
	Roe	ROE
	Recurring earning power = (before tax profits + provisions for bad debts)/total assets	RECUREARNPOWER
LIQUIDITY	Interbank ratio	INTERBANK
	Liquid assets/ total deposits and borrowings	LIQUASSETS_TOTDEPBOR
	Liquid assets/ customer and short term funds	LIQUASSETS_CSTFUND
	Net loans/ customer and short term funds	NL_CSTFUND
	Net loans/ total deposits and borrowings	NL_DEPBOR

Table 6. Financial Deterioration and Early Indicators: Univariate Regressions

Model Specification: Prob $\{Y_i = 1\} = \Phi(\alpha + \beta X_i)$

This table shows simple logit estimation results where the dependent variable is separately regressed on each explanatory variable and a constant. Group A corresponds to the sub-sample of banks that are from Egypt, Jordan, Lebanon, Morocco, or Tunisia, Group B corresponds to the sub-sample of banks that are from Bahrain, Kuwait, Oman, Qatar, Saudi Arabia or United Arab Emirates, and Group C corresponds to the sub-sample of banks that are from Israel or Turkey. For regional estimations, two dummy variables are added: GROUPA, which is equal to 1, if the bank belongs to Egypt, Jordan, Lebanon, Morocco, or Tunisia and 0, otherwise, and GROUPC, which is equal to1, if the bank belongs to Israel or Turkey. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10 percent level of significance, respectively. Z-Stats are in italics. The number of observations in the regional model is not equal to the sum of the number of observations of Group A, Group B, and Group C models because all data are not available for each bank, each year and each indicator.

		Whole sample	Regional dummies	Group A	Group B	Group C
CAPITAL	ΔHYBRIDCAP_LIAB	-3.260** (-2.523)	-4.154*** (-2.977)			
	ΔHYBRIDCAP_TA	-3.260** (-2.309)	-4.230*** (-2.780)			
	ΔEQU_DEPSTFUND				-0.118** (-2.085)	
	ΔEQU_LIAB				-0.132** (-2.146)	
	ΔEQU_TA				-0.236** (-2.530)	
	ΔCAPFUNDS_NL			0.131* (1.779)		
	ΔTCR					0.515** (2.052)
	ΔTIER1RATIO					0.283** (2.072)
ASSET QUALITY	ΔLLR_GL	0.133** (2.092)	0.132** (2.094)	0.577** (2.479)		
	ΔIMPLOANS_GL	0.269*** (3.167)	0.276*** (3.139)	0.424** (2.328)	0.261*** (2.618)	
	ΔLLR_IMPLOANS				-0.012* (-1.689)	
	ΔLLP_NIR					0.114*** (2.944)
	ΔLLP_GL			-2.661*** (-3.046)		
EARNINGS	ΔCOSTTOINCOME	0.069*** (3.482)	0.070*** (3.554)		0.088*** (3.649)	
	ΔINCNET_EQU	-0.071** (-2.531)	-0.074*** (-2.653)		-0.080** (-2.528)	
	ΔNONINTEXP_A	0.724** (2.222)	0.735** (2.323)		1.277*** (2.729)	
	ΔROE	-0.059** (-2.464)	-0.060*** (-2.601)	-0.116* (-1.938)	-0.083** (-2.434)	
	ΔNIM			-2.173** (-2.181)		
	ΔNONINTEXP_A			-2.633** (-2.407)		
	ΔNIR_A			-3.382*** (-2.742)		
LIQUIDITY	ΔNL_CSTFUND	-0.043* (-1.800)	-0.044* (-1.801)		-0.070* (-1.810)	
	ΔINTERBANK			0.006* (1.790)		

Table 7. Financial Deterioration and Early Indicators: Stepwise Results

Model Specification: Prob $\{Y_i = 1\} = \Phi\left(\alpha + \sum_{j=1}^{J} \beta_j C_{ji}\right)$

		Whole sample	Group A	Group B	Group C
	CONSTANT	-1.797*** (-8.584)	-2.652*** (-3.642)	-1.900*** (-6.676)	-2.081*** (-3.819)
CAPITAL	ΔEQU_DEPSTFUND				0.019* (1.786)
EARNINGS	ΔCOSTTOINCOME	0.083*** (3.522)		0.112*** (3.617)	
	ΔNIR_A		-4.466** (-2.552)		
ASSET QUALITY	ΔIMPLOANS_GL	0.241** (2.559)		0.210** (2.491)	
	ΔLLP_NIR	0.030* (1.878)			0.114*** (2.968)
	ΔLLR_GL		0.507*** (2.851)		
	ΔLLP_TA			1.363** (1.970)	
McFadden R^2		0.142	0.380	0.199	0.175
Total Observations		238	54	151	47
Number of observations with Y=1		35	8	21	7

This table shows logit estimation results where the dependent variable is regressed on a constant and the accounting indicators selected by a stepwise process. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10% level of significance, respectively. Z-Stats are in italics.

Table 8 Too Big To Fail and Effectiveness of Early Indicators

Model Specification: Prob $\{Y_i = 1\} = \Phi\left(\alpha + \sum_{j=1}^{J} \beta_j C_{ji}\right)$

		TBTF	NON TBTF
	CONSTANT	-1.575*** (-6.691)	-2.477*** (-5.136)
EARNINGS	ΔCOSTTOINCOME	0.113*** (3.429)	0.031 (0.754)
ASSET QUALITY	ΔIMPLOANS_GL	0.278** (2.430)	0.218 (1.144)
	ΔLLP_NIR	0.051** (2.434)	-0.001 (-0.030)
McFadden R^2		0.190	0.061
Total Observations		169	69
Number of observations with Y=1		30	5

This table shows logit estimation results where the dependent variable is regressed on a constant and the accounting indicators selected by a stepwise process on the whole sample of banks. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10% level of significance, respectively. Z-Stats are in italics. TBTF banks are those with a Fitch Support rating equal to 1 or 2.

Table 9. Too Big To Fail and Effectiveness of Early Indicators: New Stepwise

Model Specification: Prob $\{Y_i = 1\} = \Phi\left(\alpha + \sum_{j=1}^{J} \beta_j C_{ji}\right)$

		TBTF	NON TBTF
	CONSTANT	-1.575*** (0.235)	
EARNINGS	ΔCOSTTOINCOME	0.113*** (3.429)	
ASSET QUALITY	ΔIMPLOANS_GL	0.278** (2.430)	
	ΔLLP_NIR	0.051** (2.434)	
McFadden R^2		0.190	
Total Observations		169	
Number of observations with Y=1		30	

This table shows logit estimation results where the dependent variable is regressed on a constant and the accounting indicators selected by new stepwise processes. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10 percent level of significance, respectively. Z-Stats are in italics. TBTF banks are those with a Fitch Support rating equal to 1 or 2.

Table 9A. Too Big To Fail and Effectiveness of Early Indicators

Model Specification: Prob $\{Y_i = 1\} = \Phi\left(\alpha + \sum_{j=1}^{J} \beta_j C_{ji} + \sum_{j=1}^{J} \beta'_j C_{ji} * DUM\_TBTF \right)$

	CONSTANT	-2.477*** (-5.136)
EARNINGS	ΔCOSTTOINCOME	0.031 (0.754)
ASSET QUALITY	ΔIMPLOANS_GL	0.218 (1.144)
	ΔLLP_NIR	-0.001 (-0.030)
	DUM_TBTF	0.902* (1.680)
	DUM_TBTF* ΔCOSTTOINCOME	0.081 (1.512)
	DUM_TBTF* ΔIMPLOANS_GL	0.059 (0.267)
	DUM_TBTF* ΔLLP_NIR	0.052 (1.313)
McFadden R^2		0.186
Total observations		238
Number of observations with Y=1		35
Risk level to reject $\beta_1 + \beta_1' = 0$		3.29%
Risk level to reject $\beta_2 + \beta_2' = 0$		1.51%
Risk level to reject $\beta_3 + \beta_3' = 0$		94.75%

This table shows logit estimation results where the dependent variable is regressed on a constant and the accounting indicators selected by a stepwise process on the whole sample of banks. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10 percent level of significance, respectively. Z-Stats are in italics. The dummy variable DUM_TBTF takes the value of 1 if the bank is TBTF and 0 otherwise. TBTF banks are those with a Fitch Support rating equal to 1 or 2.

Table 9B. Too Big To Fail and Effectiveness of Early Indicators

Model Specification:
Prob

$$\left\{ Y_i = 1 \right\} = \Phi\left(\alpha + \sum_{j=1}^{J} \beta_j C_{ji} + \sum_{j=1}^{J} \beta'_j C_{ji} * DUM\_TBTF + \gamma GDPPERCAPITA + \gamma' GDPPERCAPITA * DUM\_TBTF \right)$$

	CONSTANT	-3.284*** (-3.612)
EARNINGS	ΔCOSTTOINCOME	-0.007 (-0.147)
ASSET QUALITY	ΔIMPLOANS_GL	0.254 (1.258)
	ΔLLP_NIR	-0.035 (-0.700)
	DUM_TBTF	1.544 (1.262)
	DUM_TBTF* ΔCOSTTOINCOME	0.052 (0.657)
	DUM_TBTF* ΔIMPLOANS_GL	0.033 (0.135)
	DUM_TBTF* ΔLLP_NIR	0.065 (1.179)
	GDPPERCAPITA	0.0002* (1.851)
	DUM_TBTF*GDPPERCAPITA	-0001 (-1.625)
McFadden R^2		0.116
Total Observations		179
Number of observations with Y=1		24
Risk level to reject $\beta_1 + \beta_1^{'} = 0$		3.36%
Risk level to reject $\beta_2 + \beta_2^{'} = 0$		47.33%
Risk level to reject $\beta_3 + \beta_3^{'} = 0$		3.89%
Risk level to reject $\gamma + \gamma' = 0$		19.48%

This table shows logit estimation results where the dependent variable is regressed on a constant and the accounting indicators selected by a stepwise process on the whole sample of banks. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10 percent level of significance, respectively. Z-Stats are in italics. The dummy variable DUM_TBTF takes the value of 1 if the bank is TBTF and 0 otherwise. TBTF banks are those with a Fitch Support rating equal to 1 or 2.

Table 9C. Too Big To Fail and Effectiveness of Early Indicators: New Stepwise

Model Specification: Prob $\{Y_i = 1\} = \Phi\left(\alpha + \sum_{j=1}^{J} \beta_j C_{ji}\right)$

		TBTF	NON TBTF
	CONSTANT	-1.74**	-3.284***
		(-2.124)	(-3.612)
EARNINGS	ΔCOSTTOINCOME	0.045	-0.007
		(0.717)	(-0.147)
ASSET QUALITY	ΔIMPLOANS_GL	0.287**	0.254
		(2.065)	(1.258)
	ΔLLP_NIR	0.030	-0.035
		(1.296)	(-0.700)
	GDPPERCAPITA	$3.57*10^{-6}$	0.0002*
		(0.065)	(1.851)
McFadden R^2		0.089	0.181
Total observations		128	51
Number of observations with Y=1		19	5

This table shows logit estimation results where the dependent variable is regressed on a constant and the accounting indicators selected by new stepwise processes. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10 percent level of significance, respectively. Z-Stats are in italics. TBTF banks are those with a Fitch Support rating equal to 1 or 2.

Table 9D. Bank Size and Effectiveness of Early Indicators

Model Specification: Prob $\{Y_i = 1\} = \Phi\left(\alpha + \sum_{j=1}^{J} \beta_j C_{ji}\right)$

		Large banks	Small banks
	CONSTANT	-2.121*** (-7.310)	-1.707*** (-5.116)
EARNINGS	ΔCOSTTOINCOME	0.110*** (3.692)	0.049 (1.190)
ASSET QUALITY	ΔIMPLOANS_GL	0.009 (0.069)	0.329*** (2.841)
	ΔLLP_NIR	0.051** (2.430)	0.017 (1.123)
McFadden R^2		0.154	0.168
Total Observations		147	91
Number of observations with Y=1		20	15

This table shows logit estimation results where the dependent variable is regressed on a constant and the accounting indicators selected by a stepwise process on the whole sample of banks. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10 percent level of significance, respectively. Z-Stats are in italics. Large banks are those with total assets greater than the median value that is 5160.48 million USD for banks belonging to Group A (Egypt, Jordan, Lebanon, Morocco, and Tunisia), 5502.85 million USD for banks belonging to Group B (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and United Arab Emirates), and 17 268.10 million USD for banks belonging to Group C (Israel and Turkey).

Table 9E. Bank Size and Effectiveness of Early Indicators: New Stepwise

Model Specification: $\text{Prob}\{Y_i = 1\} = \Phi\left(\alpha + \sum_{j=1}^{J} \beta_j C_{ji}\right)$

		Large banks	Small banks
	CONSTANT	-2.101*** (-7.480)	-1.960*** (-5.033)
CAPITAL	ΔEQU_NL	0.061* (1.892)	
EARNINGS	ΔCOSTTOINCOME	0.114*** (4.004)	
	ΔNIR_A		-0.537* (-1.783)
ASSET QUALITY	ΔLLP_NIR	0.041* (1.901)	
	ΔIMPLOANS_GL		0.411*** (3.540)
LIQUIDITY	ΔLIQUASSETS_CSTFUND		0.057** (2.118)
McFadden R^2		0.149	0.203
Total Observations		161	92
Number of observations with Y=1		21	14

This table shows logit estimation results where the dependent variable is regressed on a constant and the accounting indicators selected by new stepwise processes. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10 percent level of significance, respectively. Z-Stats are in italics. Large banks are those with total assets greater than the median value that is 5160.48 million USD for banks belonging to Group A (Egypt, Jordan, Lebanon, Morocco, and Tunisia), 5502.85 million USD for banks belonging to Group B (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and United Arab Emirates), and 17 268.10 million USD for banks belonging to Group C (Israel and Turkey).

Table 10. Structure of Bank Assets and Effectiveness of Early Indicators

Model Specification: Prob $\{Y_i = 1\} = \Phi\left(\alpha + \sum_{j=1}^{J} \beta_j C_{ji}\right)$

		Net loans/ Total assets low	Net loans / total assets high
	CONSTANT	-2.083*** (-5.911)	-1.593*** (-5.856)
EARNINGS	ΔCOSTTOINCOME	0.073** (2.373)	0.114** (2.847)
ASSET QUALITY	ΔIMPLOANS_GL	0.332** (2.077)	0.169* (1.697)
	ΔLLP_NIR	0.021 (1.041)	0.035* (1.737)
McFadden R^2		0.226	0.090
Total Observations		122	116
Number of observations with Y=1		15	20

This table shows logit estimation results where the dependent variable is regressed on a constant and the accounting indicators selected by a stepwise process on the whole sample of banks. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10 percent level of significance, respectively. Z-Stats are in italics. The ratio Net loans/ total assets is considered as low if it is lower than its median value and it is considered as high if it is greater than its median value. This median value is equal to 39.41 percent for banks belonging to Group A (Egypt, Jordan, Lebanon, Morocco, and Tunisia), 52.26 percent for banks belonging to Group B (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and United Arab Emirates), and 56.04 percent for banks belonging to Group C (Israel and Turkey).

Table 11. Structure of Bank Assets and Effectiveness of Early Indicators: New Stepwise

Model Specification: Prob $\{Y_i = 1\} = \Phi\left(\alpha + \sum_{j=1}^{J} \beta_j C_{ji}\right)$

		Net loans/ Total assets low	Net loans / total assets high
	CONSTANT	-2.121*** (-5.794)	-1.726*** (-6.648)
EARNINGS	ΔCOSTTOINCOME	0.064** (2.342)	
	ΔROE		-0.137** (-2.529)
ASSET QUALITY	ΔIMPLOANS_GL	0.342** (2.391)	
LIQUIDITY	ΔLIQUASSETS_CSTFUND	0.025* (1.658)	
McFadden R^2		0.218	0.064
Total Observations		124	130
Number of observations with Y=1		15	21

This table shows logit estimation results where the dependent variable is regressed on a constant and the accounting indicators selected by new stepwise processes. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10 percent level of significance, respectively. Z-Stats are in italics. The ratio Net loans/ total assets is considered as low if it is lower than its median value and it is considered as high if it is greater than its median value. This median value is equal to 39.41 percent for banks belonging to Group A (Egypt, Jordan, Lebanon, Morocco, and Tunisia), 52.26 percent for banks belonging to Group B (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and United Arab Emirates), and 56.04 percent for banks belonging to Group C (Israel and Turkey).

Table 12. Structure of Bank Liabilities and Effectiveness of Early Indicators

Model Specification: Prob $\{Y_i = 1\} = \Phi\left(\alpha + \sum_{j=1}^{J} \beta_j C_{ji}\right)$

		Deposits/ total assets low	Deposits/ total assets high
	CONSTANT	-1.672*** (-5.571)	-1.922*** (-6.393)
EARNINGS	ΔCOSTTOINCOME	0.093*** (3.189)	0.073 (1.602)
ASSET QUALITY	ΔIMPLOANS_GL	0.466*** (2.677)	0.116 (1.093)
	ΔLLP_NIR	0.026 (0.895)	0.033 (1.531)
McFadden R^2		0.228	0.075
Total Observations		121	117
Number of observations with Y=1		20	15

This table shows logit estimation results where the dependent variable is regressed on a constant and the accounting indicators selected by a stepwise process on the whole sample of banks. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10 percent level of significance, respectively. Z-Stats are in italics. The ratio Deposits/ total assets is considered as low if it is lower than its median value and it is considered as high if it is greater than its median value. This median value is equal to 86.36 percent for banks belonging to Group A (Egypt, Jordan, Lebanon, Morocco, and Tunisia), 82.28 percent for banks belonging to Group B (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and United Arab Emirates), and 80.70 percent for banks belonging to Group C (Israel and Turkey).

Table 13. Structure of Bank Liabilities and Effectiveness of Early Indicators: New Stepwise

Model Specification: Prob $\{Y_i = 1\} = \Phi\left(\alpha + \sum_{j=1}^{J} \beta_j C_{ji}\right)$

		Deposits/ total assets low	Deposits/ total assets high
	CONSTANT	-1.629***	-2.144***
		(-5.995)	(-6.874)
CAPITAL	ΔEQU_TA	-0.264**	
		(-2.232)	
EARNINGS	ΔOTHOPINC_A		-2.033**
			(-2.219)
	ΔNIR_A		-1.477**
			(-2.098)
ASSET QUALITY	ΔLLR_GL	0.331***	
		(2.705)	
McFadden R^2		0.067	0.073
Total Observations		114	124
Number of observations with Y=1		17	14

This table shows logit estimation results where the dependent variable is regressed on a constant and the accounting indicators selected by new stepwise processes. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10 percent level of significance, respectively. Z-Stats are in italics. The ratio Deposits/ total assets is considered as low if it is lower than its median value and it is considered as high if it is greater than its median value. This median value is equal to 86.36 percent for banks belonging to Group A (Egypt, Jordan, Lebanon, Morocco, and Tunisia), 82.28 percent for banks belonging to Group B (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and United Arab Emirates), and 80.70 percent for banks belonging to Group C (Israel and Turkey).

Table 14. Structure of Bank Liabilities and Effectiveness of Early Indicators

Model Specification: Prob $\{Y_i = 1\} = \Phi\left(\alpha + \sum_{j=1}^{J} \beta_j C_{ji}\right)$

		Market funded liabilities/ total assets low	Market funded liabilities/ total assets high
	CONSTANT	-1.590*** (-5.773)	-2.114*** (-6.117)
EARNINGS	ΔCOSTTOINCOME	0.027 (0.713)	0.121*** (3.735)
ASSET QUALITY	ΔIMPLOANS_GL	0.213* (1.924)	0.282* (1.735)
	ΔLLP_NIR	0.027 (1.105)	0.038* (1.767)
McFadden R^2		0.073	0.243
Total Observations		112	126
Number of observations with Y=1		17	18

This table shows logit estimation results where the dependent variable is regressed on a constant and the accounting indicators selected by a stepwise process on the whole sample of banks. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10 percent level of significance, respectively. Z-Stats are in italics. The ratio Market funded liabilities/ total assets is considered as low if it is lower than its median value and it is considered as high if it is greater than its median value. This median value is equal to 5.84 percent for banks belonging to Group A (Egypt, Jordan, Lebanon, Morocco, and Tunisia), 4.27 percent for banks belonging to Group B (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and United Arab Emirates), and 10.50 percent for banks belonging to Group C (Israel and Turkey).

Table 15. Structure of Bank Liabilities and Effectiveness of Early Indicators: New Stepwise

Model Specification: Prob $\{Y_i = 1\} = \Phi\left(\alpha + \sum_{j=1}^{J} \beta_j C_{ji}\right)$

		Market funded liabilities/ total assets low	Market funded liabilities/ total assets high
	CONSTANT	-1.629*** (-5.995)	-2.114*** (-6.117)
CAPITAL	ΔEQU_TA	-0.264** (-2.232)	
EARNINGS	ΔCOSTTOINCOME		0.121*** (3.735)
ASSET QUALITY	ΔIMPLOANS_GL		0.282* (1.735)
	ΔLLR_GL	0.331*** (2.705)	
	ΔLLPROV_NIR		0.038* (1.767)
McFadden R^2		0.067	0.243
Total Observations		114	126
Number of observations with Y=1		17	18

This table shows logit estimation results where the dependent variable is regressed on a constant and the accounting indicators selected by new stepwise processes. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10 percent level of significance, respectively. Z-Stats are in italics. The ratio Market funded liabilities/ total assets is considered as low if it is lower than its median value and it is considered as high if it is greater than its median value. This median value is equal to 5.84 percent for banks belonging to Group A (Egypt, Jordan, Lebanon, Morocco, and Tunisia), 4.27 percent for banks belonging to Group B (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and United Arab Emirates), and 10.50 percent for banks belonging to Group C (Israel and Turkey).